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Chapter 5: The integration of machine learning to streamline manufacturing and improve quality assurance

5.1. Introduction

The market for consumer-oriented products is becoming increasingly competitive. To maintain or gain market share, manufacturers are under pressure to improve quality and reduce costs. Social and political factors increase product life cycles and encourage manufacturers to pay more attention to the whole production process. It becomes increasingly common to integrate certain processes of manufacturing automation to respond to more and more sophisticated requests, such as flexible and versatile production at high-quality coordination of design, quality assurance, and production planning. In modern production and business control, the drivers towards greater competitiveness are considered global and adaptive supply chain management (Kang et al., 2018; Tao et al., 2018; Lee et al., 2019).

Due to fast market changes and shorter product life cycles, the goal of manufacturing and design integration is to keep the design process in synchronization with the production process, which is initiated at the beginning of the product design phase. This is done by passing the feedback of the capabilities and constraints of the production process to the designers so that proper design decisions are made. A central tenet of concurrent engineering is to bring people and information together so that constraints once considered. Here, we focus on the area of design and manufacturing integration, which is an important subarea of CE. Integration can be defined as merging branches of a service to improve performance at higher levels. The ultimate goal of the integration of design and manufacturing is to have a common set of corporate-wide optimal design and manufacturing decisions that leads to corporate-wide performance optimization at lower levels since the system's cost is inversely proportional to the performance level at which the integration is done (Zhong et al., 2017; Xu et al., 2018).

5.1.1. Background and Significance

Multiple processes are required to manufacture an end-item product. These processes in a typical manufacturing environment can include machining, assembly, welding, soldering, coating, material handling, inspection, and finishing. The process of producing the product design is in general done by engineering personnel. The design concepts then undergo iterative changes until the best technical solution is fully evolved and established in the form of detailed drawings and specifications that can be used to manufacture the product. This phase is often referred to as product development. The subsequent process of the physical realization of the product from materials is referred to as the manufacturing phase. Manufacturing of products involves a great deal of effort. Quality and reliability of products and services, which are deemed to be satisfactory by the customers, are mainly associated with how the products are manufactured. It is a natural desire for any manufacturer to ensure that their products are manufactured with the best possible quality and reliability. Quality control is thus an essential function of manufacturing management.

In recent years, there have been many developments in techniques, procedures, and methods used in the tasks and activities associated with production. These advances are mainly facilitated by the introduction of computers. Computerized tools that help product designers or engineers of manufacturers to carry out in a compact and integrated manner all the variables and parameters in the numerous tasks, interactions, and decisions of product design and development related to quality and reliability are known as CAD/CAM tools. CAD/CAM tools have been developed to be implemented into manufacturing processes such as machining, assembly, welding, soldering, and coating, enabling them to be in effect computer-aided or finalized. Various modern techniques for quality assurance have emerged, allowing companies to have a more efficient means for quality systems. These techniques include quality function deployment, failure-mode effects analysis, Reliability, Maintainability, and Supportability engineering, and fault-tolerant system technique.

5.2. Overview of Manufacturing Processes

Manufacturing is concerned with the technological and economic processes involved in the transformation of raw materials into products. It transforms energy and materials from nature into engineering systems that provide the functions desired by society. A product is defined as an ensemble of parts that assemble to give the product its functionality, that are manufactured according to established performance, cost, and quality thresholds and standards; complying with rules for the safety of persons in the operational activity, with rules for safety of the environment, and with rules regarding other externalities not directly connected to the product process. The parts that comprise the product itself may be defined as bulk components, sheets, molded, or a combination thereof. Parts can also be sub-assemblies or assemblies made by the mechanical assembly and engineering systems that accompany the product.

Manufacturing can be described as a series of interrelated processes that reside on a factory floor. A transformation system takes as input work-in-progress in the form of materials, existing components, information, or a combination thereof. The output is finished products, sub-assemblies, or assemblies. The result of a transformation is the geometric and physical attributes of the product as a consequence of cycles involving motion, monitoring, waiting, and action. Before geometric attributes are defined, the part undergoes rough machining and finish machining cycles during which the material properties develop. The tools used during the machining cycle are cutting tools whose geometry defines the resulting product attributes and are constantly monitored to take into account wear during the cycle. The attributes of the tool and the applied process parameters are the main elements that define the length of the machining cycle and the resulting product quality. However, the entire process can only be understood if the geometry of the cutting tool is applied, considering the physical attributes and the features of the bulk and sheet materials used.

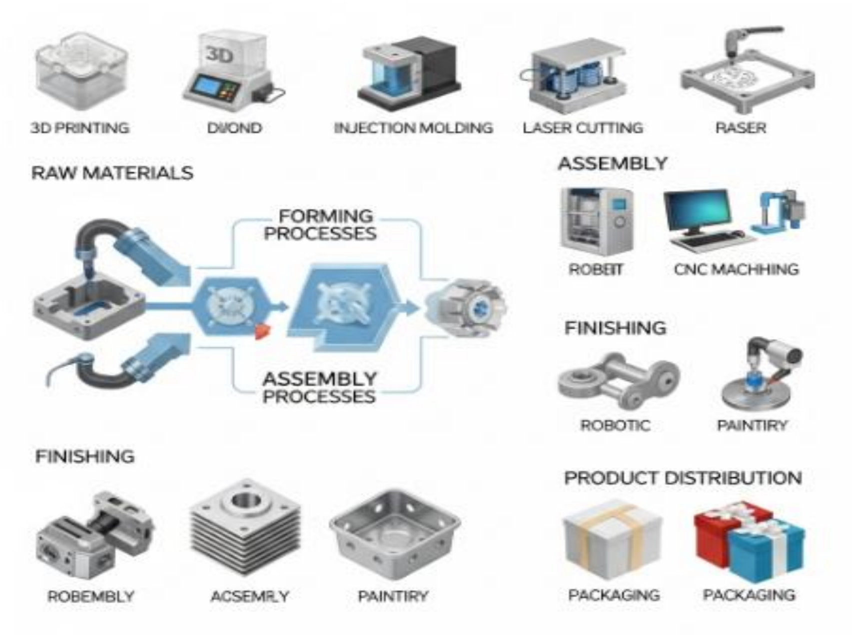

Fig 5.1: Overview of Manufacturing Processes.

5.2.1. Traditional Manufacturing Techniques

The manufacturing sector is one of the oldest in the world. Making goods as a company and selling them to customers who need them is the foundation of every business on the planet. The beginning of the creation of things started with an artisan and his hand tools. At that time, it was the artisan himself who shaped the product according to customer requirements and requests. He was flexible but expensive and therefore limited to a small number of pieces. Therefore, the birth of industry came with the need to produce on a larger scale, with shorter time delivery at a lower cost. As a result, the artisan was replaced by mass-production manufacturers. The initial production model consisted of a system of simple tasks divided among multiple employees, in the same space as the craftsman, to produce at lower unit cost. Later, developments in mechanization and the implementation of high-volume production lines increased product standardization. Basically, the mass production system became a system of mass production systems, equipped with highly specialized machines, where the ability to determine machine and operation characteristics was given to engineers.

The flexibility lost in the mass production system started to be recuperated with the implementation of Numerical Control machines. With NC, and especially CNC machine tools the machine was equipped with the ability to modify its behavior according to customers or production requirements. The automation allowed for a better utilization of the resource which enabled the adoption of production systems designed for low-volume production tasks such as craft systems, without the associated high unit cost. However, during the eighties new competitors were emerging in the low-cost markets. New countries that could supply low unit cost. The manufacturers aimed to push production volumes to the lowest levels possible, thus reducing production costs. Instead of competition at low prices, the development of high quality at low cost was the road to follow. Unexpectedly, a higher proliferation of products was demanded by the markets with shorter time to deliver, together with the need for low product costs.

5.2.2. Emerging Trends in Manufacturing

Over the last decade, the manufacturing landscape has undergone significant change with the incorporation of augmented reality, robotics and cobots, and artificial intelligence and machine learning. This change was intensified as a consequence of the pandemic, which forced major portions of the global workforce to stay at home, hampering the workforce and operational capacity of many manufacturers, particularly in the traditional sectors. This shortage elevated labor costs, which accelerated the movement toward automation in regions that have historically enjoyed competitive salary advantages. This shift to automation, however, has been more evident in developed countries, where many companies are increasingly adopting solutions enabled by augmented reality, robotics, artificial intelligence, and machine learning. It has been noted that the increased focus on digital manufacturing solutions will not decrease after the pandemic. Digital solutions will be the key driver for recovery and growth and will help regain its pole position in the Asia-Pacific market, overcoming the losses due to the crisis.

Augmented reality technology allows the introduction of additional information into the eye of the user when analyzing the surrounding environment. As a consequence, an augmented reality-supported system can insert virtual objects into the real environment and interact with the human user for better understanding and decision-making. For example, an augmented reality application has been proposed to guide operators in complex factory assembly processes, which is an essential part of the operation of many high-tech multistage assembly processes for precision electronic products, such as mobile phones, computers, and reasonable and feasible robots with simple augmented reality equipment. Using augmented reality technology to support manual assembly operations may improve operators' cognitive load reduction and task performance. Artificial intelligence, Industrial Intelligence, and explained artificial intelligence are becoming hot development fronts in the intelligentization and automation process in manufacturing systems.

5.3. Understanding Machine Learning

Whether explicitly or not explicitly stated, machine learning, or ML, is an increasingly adopted technology in Industry 4.0, which aims to intelligently connect people, things, and systems to foster the flexibility and efficiency of the manufacturing process. Deep learning (DL), or deep neural networks, is a special case of ML, but the terms ML and DL are often mistaken as the same technology. In addition to the research and development of ML-DL algorithms themselves, other critical technologies for intelligent automation and integration of ML-DL-driven systems into the manufacturing process include data hosting platforms, data preprocessing algorithms, computing resources provided by the edge/cloud, and cybersecurity and privacy-preserving mechanisms.

There are multiple types of ML-DL algorithms with varying levels of supervision, interpretability, difficulty of training, data size requirements, etc. Regardless of the specific type of algorithms, training an ML model requires special modeling considerations. The modeling considerations are critical to the success of deploying ML in manufacturing, but these considerations are not explicitly mentioned in scientific papers that focus on developing new types of ML algorithms. However, the modeling considerations are often explicitly or implicitly covered in applied ML-DL engineering textbooks, which serve as good references for a general audience. Due to space limitations, we only provide a high-level overview of ML-DL algorithms and modeling considerations via a short summary.

5.3.1. Definition and Key Concepts

Machine learning is a field of computer science that involves the statistical modeling of data to create computer programs that can analyze data, recognize and learn patterns, and predict outcomes with reasonable accuracy. These patterns may be complex, encompassing multidimensional relationships that are difficult to mathematically express directly, and the predictions may be uncertain. Machine learning is an extension of some of the classical techniques and concepts in statistics, computer science, and optimization theory, and it differs from those classical approaches in that machine learning emphasizes enhancing performance automatically as more data becomes available rather than relying on a predefined set of rules. As a result, machine learning is often part of a larger software system and is applied to software problems where there is a significant amount of complex data. For a problem to be solved via machine learning, a large amount of typical past data must be gathered; this data can be labeled as showing user preference or outcome. During the training or algorithm-learning phase, a model is configured based on this past data, and then it is used to predict user outcomes for new data.

The most frequently used types of machine learning are supervised learning, unsupervised learning, and reinforcement learning. The primary focus of this essay is on supervised machine learning for classification and regression problems and reinforcement learning, which is well-suited for knowledge-based decision problems, such as autonomous driving. The supervised learning paradigm relies on training datasets that contain a set of known labels or solution parameters based on the problem domain data.

5.3.2. Types of Machine Learning

The two primary types of machine learning, supervised and unsupervised learning, differ in the way they interpret the data. The main characteristic of supervised learning is that an algorithm acts on some input data and generates output in a specific field. This corresponds to a database that can consist of numerical data or discrete categorical data. The use of supervised learning is mainly predictive meaning that it will analyze the data to build a model to predict future outcomes. In this case, the model helps us answer the question "What do we think will happen?" We can apply supervised learning in various applications, for example, to predict stock prices, airplane delays, times of seismic activity, etc.

Unlike supervised learning, in unsupervised learning, there is no answer to learning, and there are no variables to predict. At this stage, there are only input variables (also called features), which means a database is optimized to describe the variables of interest. Therefore, the unsupervised approach is crucial to help understand what is happening in the dataset in order to carry out the next steps in the data analysis project. In this case, the model helps answer the question "What is happening in the data set?" Unsupervised learning is used to discover patterns present in data such as clustering customers or observing how a disease evolves. Associative rule learning, clustering, dimensionality reduction, least squares, expectation-maximization algorithm, and k-means are examples of unsupervised learning techniques. In addition to the supervised and unsupervised type approaches, machine learning algorithms differ based on the function of the learning task. There are algorithms for classification, regression, handling missing values, inducing relation, density estimation, and probability estimation. We have already mentioned classification and regression in the very first paragraph about the supervised and unsupervised tasks.

5.4. Applications of Machine Learning in Manufacturing

Manufacturing has been the background for many innovations and pioneering applications of Machine Learning. The ability of this technology to learn functional relationships from vast amounts of data, including temporal data, has helped the application of business process management in manufacturing. These types of techniques are very useful for Predictive Maintenance, Quality Control and Assurance, Supply Chain Optimization, and Scheduling.

Maintenance has always been a focus of interest in many industries. For the manufacturers, even with a low margin, postponing activities intended to keep machines running may harm operations, causing unexpected shutdowns, long delays, and other issues. Therefore, the adoption of solutions that avoid unexpected maintenance becomes crucial. Traditionally, maintenance has been reactive, responding to machines' behavior. With the increase in the utilization of sensors, it became possible to adopt monitoring solutions, which are called Predictive Maintenance or Condition-Based Maintenance. Since the 1980s, several statistical models have been used to predict machine failures. However, with the rapid development of Machine Learning, its algorithms have been employed for this function, including Neural Networks, Decision Trees, Ensemble Learning, and others.

Quality Inspection has become a focus for Machine Learning applications. With the utilization of cameras and image processing, the analysis of images is an important topic in quality assurance because it remains a significant challenge in manufacturing. Human workers are still the default solution adopted by manufacturers for quality inspection due to the limitations of cameras, such as lighting or angle of view.

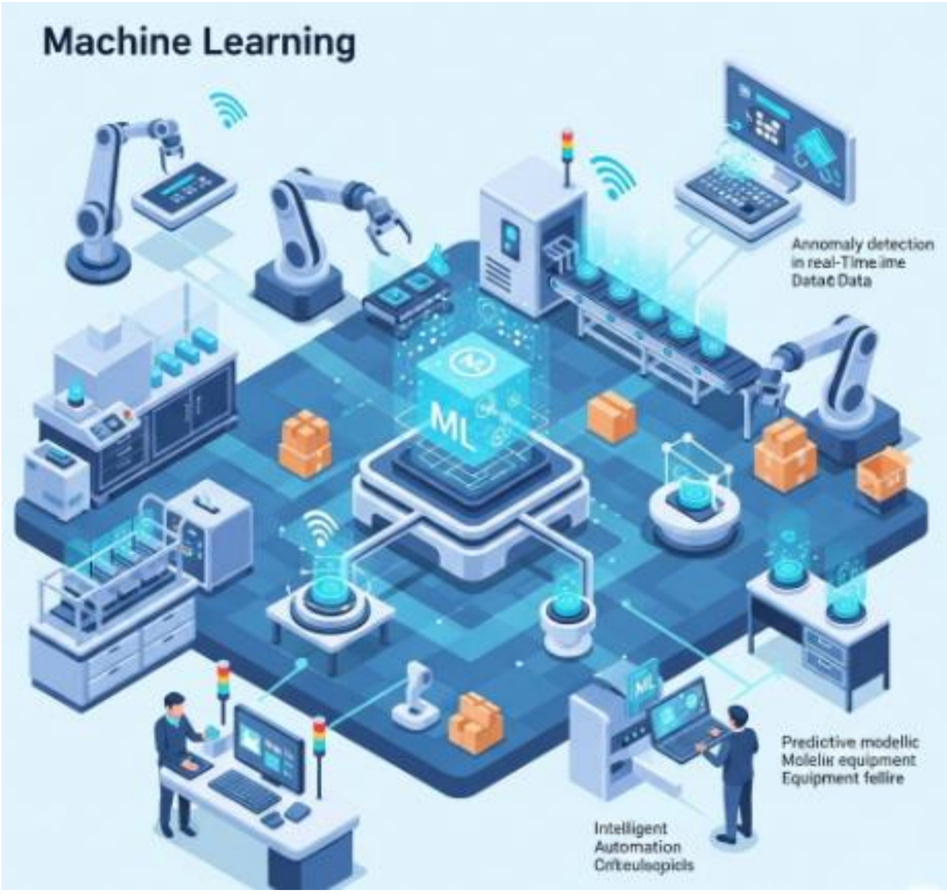

Fig 5.2: Applications of Machine Learning in Manufacturing.

5.4.1. Predictive Maintenance

Among these applications, predictive maintenance is one of the major areas of concern to manufacturers, since machine service has a large impact on the manufacturing process and its cost. Maintenance and service-related expenditures account for 18% of total costs in the manufacturing sector, as well as for the 2nd greatest expense after sales cost. Further, because traditional maintenance services rely on static service schedules to avoid machine breakdown, the fixed schedules can lead to either over-maintenance or under-maintenance by the manufacturer. Thus, there is an increasing demand for the development of novel intelligent predictive maintenance services to streamline predictive maintenance efficiency, increasing functioning machine time as well as reducing costs.

Traditional predictive maintenance systems are not able to provide real-time detection and accurate prediction of machine problems, tasks that are crucial to successful production. Novel predictive maintenance approaches integrating available data with advanced integrated algorithms leveraging machine learning or AI methods are starting to replace conventional solutions. With advanced-level data analytics in predictive maintenance, achieving enhanced success is possible by improving the prediction of parts' life cycles and item failures more accurately. Other predictive maintenance models leverage sensor measurement data and advanced machine learning models to increase prediction accuracy. In addition, other studies propose methodologies for machine fault prediction employing deep learning methods. With global digitization, there is an increasing amount and availability of manufacturing machine failure and operating data collected from sources.

5.4.2. Quality Control and Assurance

Machine learning is having an increasingly important impact on quality control. In industrial settings, managed queues and production environments must be capable of detecting and debunking the failure of production processes, to preserve special product characteristics, hence safeguarding the functionality of the produced goods. While the application of complex algorithms for quality inspection is still rare in production, traditional, straightforward rules are often the means of choice. The provisional implementation of unverified heuristic rules in production ensures both simple maintainability by production personnel and the option for retrospective optimization of quality gates. This inclination toward easier-to-manage quality gates is observable in many applied applications. Together with the wide availability of smartphone cameras, quality inspection with machine learning is forecasted to prevail in many industrial use cases in the future.

The industrial implementation also entails several hurdles. Quality inspection algorithms are typically highly data-hungry, needing large amounts of data for training. If it is possible to support the computer-aided inspection with well-running human visual control, it is possible to create a large training database. Further on, while the manual camera calibration for operator inspection might be a human-intensive process, the outcome is an optimized hardware and software solution for operator-staffed visual control that requires nearly no investment to be transferred into industrial production. Further on, even the introduction of ML into quality inspection systems must not offer unreasonable or unwarranted gains. Inherent risks accompany every quality inspection system that must be kept in mind when introducing an ML solution. In the worst-case scenario, faulty quality inspection will lead to contaminated dispatch products, which potentially endangers life and limb.

5.4.3. Supply Chain Optimization

The application of machine learning has enabled vast improvements in the efficiencies of components throughout the manufacturing process. These improvements go beyond just equipment and tools on the factory floor. Instead, the systems that supply materials and rely on a plant's output also benefit from machine learning. One of the most efficient productivity improvement programs within manufacturing is the just-in-time (JIT) philosophy. JIT seeks to minimize inventory required by suppliers and manufacturers, thus cutting down on costs through reduced waste and a more streamlined operation. Although the principles of JIT have existed for decades, the incorporation of machine learning within these systems has demonstrated considerable advantages.

Directly related to supplier considerations is the choice of suppliers as well as the management of supplier performance over time. Machine learning just-in-time (JIT) process optimizes many resource-intensive tasks. This technology process achieves advanced operational efficiency through continuous monitoring of the tasks affecting costs and time savings, predictive analytics to adjust plans based on dynamic changes that occur in the course of all production orders, and insight into internal processes with artificial intelligence-based decision support. A JIT machine learning process integrates all strategic production factors, such as production capacity, routing, surge orders management, demand changes notification, instant capacity changes management, and machine learning recommendations to accelerate the JIT process and reduce costs.

In the area of supplier performance management, the use of machine learning for performance scoring supplier capabilities has been proposed. It has been demonstrated that supplier scoring, which utilizes an ensemble of algorithms, can outperform traditional scoring methods. The aim is to offer effective and efficient solutions for the development of supply chain capabilities in the automotive industry.The use of machine learning for supplier selection has also been reviewed, with a comparison to deep learning methods. It has been affirmed that despite the past two decades of substantial academic research and important managerial implications, supplier selection still remains a popular subject of ongoing research but a challenge for deploying actual solutions.

5.5. Benefits of Machine Learning in Manufacturing

Aggressive innovations in technologies based on microcontrollers and information technology are being applied to major technical fields such as biological information, energy resources, and advanced materials. Low-cost, high-speed information technology has been applied to these fields, including the use of distributed sensor networks, broadband wireless data transmission, and computer integration. Manufacturing is one of the most important sectors of human activities. The development of automated, computerized control systems has advanced considerably, covering sectors from individual fabrication processes up to nearly total enterprise integration. Over the last few years, machine learning has emerged as a promising tool for performing important predictive inferences in a variety of scientific and commercial domains. The rapid pace of development in machine learning, combined with the emphasis on laying the foundations for a new model of computational and integrated manufacturing, has created a unique convergence that offers new possibilities for knowledge and data-driven product design and system integration.

The application of sensor-based data-driven machine learning approaches in manufacturing is attractive when the relationship between the inputs and outputs is of high complexity. Moreover, when physical models cannot fully capture this relationship, we believe that machine learning will play a substantial role in the manufacturing environment of the future. In addition, the application domains such as quality control, diagnostics, prognosis, or process control in which machine learning has been applied for decades will benefit further from the emerging machine learning technologies. This integration of models and data is enabling a new generation of manufacturing products and processes, built at the intersection of statistical inference and machine learning, sensor information and model-based reasoning, sophisticated modeling, and mathematical modeling technology.

5.5.1. Increased Efficiency

Implementing machine learning in the manufacturing process reduces unnecessary labor and errors, which contributes positively to the overall efficiency of the company. The flawless implementation of production plans depends on several factors, including internal equipment and operational processes, availability and quantity of raw materials, availability of commercially possible production alternatives, as well as environmental conditions like weather, national holidays, and other important local or sociocultural events. All these factors have external, unpredictable, and unmanageable influences beyond the control of manufacturers. These erratic waits for materials or production process elements create negative effects on the schedules of operations such as expected processing time, transit time, absolute tardiness, and minimum makespan. They increase production costs and affect the entire supply chain if those increases are not accommodated by customers. Such increases create a ripple effect through manufacturers, their suppliers, and the people who carry out downstream services.

The introduction of artificial intelligence applications in production process planning and scheduling is progressively improving the overall control of the various work centers that execute the operations of the production schedule. With better control and coordination of the execution of production schedules, the expected time for each internal element and each operation of a product will be reduced. Unforeseeable delays can be anticipated and hopefully avoided allowing, at best, a condition of negligible tardiness. This is the condition in which minimizing the makespan is perfectly correlated to minimizing the costs of the production processes because no internal defect will impact the entire work center both in terms of efficiencies lost on the utilization of resources, but mostly from the minuses associated with the payment of workers affected by the delay in production.

5.5.2. Cost Reduction

One of the more apparent impacts that machine learning has on manufacturing is the reduced costs associated with inventory and resources. As further advancements around machine learning and AI domains arise in conjunction with big data generation, manufacturing companies can devise better models that predict market demand and therefore are able to make better-informed decisions based on accurately predicting the demand to produce and minimize excess goods. Fewer excess goods entail lower storage costs for companies while also reducing waste from spoilage depending on the type of market the excess goods might be from, whether it is food, wholesale consumer goods, or any other product with an expiration time, molds, or obsolescence. Another benefit companies experience by predicting demand more accurately is financial, since it reduces excess material costs associated with the production and storage of excess goods.

From a general perspective, minimizing the required excess stock can be the difference between success and failure for many manufacturing companies, since excess stock might cost a company more than what it is ultimately worth and creates excess work when it comes to restocking and rotation. A good model can help reduce a company’s holding cost, and allow the business to invest the capital it saves in other parts of the business or other areas that require focus. Maintaining a suitably low level of inventory and supply chain are essential to ensure the best product supply at the most efficient costs. Fortunately, through advanced machine learning vendors and investors can help grow the business's demand and supply processes and achieve cost efficiency.

5.5.3. Enhanced Product Quality

The ability to improve product quality is a major advantage. Any manufactured item serves a specific function. If it is incapable of serving that function, its utility is adversely affected. Product failure can be tantamount to a major disaster—consider an explosive shell malfunctioning, a cancer diagnostic detection kit failing to detect the disease, or an airplane crashing because of a control system defect. Ordinarily, products are developed based on very specific specifications. Most products have tolerances indicated; for example, for electrical components, the specified or indicated values of resistance can deviate by a small percentage. The proportion of items failing or outside tolerances should be very small; even so, such failures may result in monetary losses or even serious consequences.

ML can minimize product quality issues. ML is interdisciplinary; it utilizes concepts from statistics, applied mathematics, and computer science. The crux of ML is its ability to learn from data. If one has sufficient data about failures either in operation or production, ML algorithms can be trained to either predict such anomalies or identify faulty items in real-time or at the factory floor end. Such predictions can mitigate product failures. By advancing product quality, ML will also enhance profits.

An item's functionality is generally linked to a set of measurable quality parameters. For example, the parameter controlling a plastic covering resistance to failure may be thermal conductivity or strength. If it is known beforehand that such parameters are linked to certain test conditions, and the manufactured item is subjected to such tests, the manufactured items can be classified as doing the appropriate work over the required period. Suppose that the model defining the links is given as a function F, and during testing, the output of the function is compared with threshold parameter values.

5.6. Challenges in Implementing Machine Learning

While machine learning can be powerful, there are several challenges to keep in mind for your organization. Machine learning requires a substantial amount of high-quality data, particularly labeled data, to train predictive models. If your data is not representative of the scenarios that typically occur in your manufacturing process, the model may not generalize well. Constructing high-quality training datasets can be laborious and often involves the guidance of engineers and domain experts. Labeling and data processing pipelines may not exist for your data and may need to be constructed, which involves significant additional effort. Furthermore, your labeled data may be subject to bias and inaccuracies, which can degrade the performance of machine learning models. In these cases, such as when predicting defects or failures, it is important to investigate the accuracy of any available labels derived from automated processes that may introduce errors. In many cases, organizations choose to experiment with small amounts or subsets of data, due to resource costs, or impracticality with employing domain expertise on thousands of samples. The decision of what amounts of data to use should take into account the challenges posed by the data. Additionally, some machine-learning algorithms struggle particularly when they are trained on small datasets that are meant to be broadly predictive, and bias-variance tradeoffs must be taken into account.

Integrating new machine-learning processes successfully into the existing manufacturing pipeline will likely require significant engineering attention, such as rethinking how your data is processed, labeled, extracted, and monitored over time. Existing data management structures may need updates or major changes to accommodate and collect new data types. For example, you may not currently collect raw images of parts during processing, which would be needed to create a defect-detection model. What additional data should you keep, and how should you change your data-collection protocols? What efficiency losses are acceptable while gathering this new data?

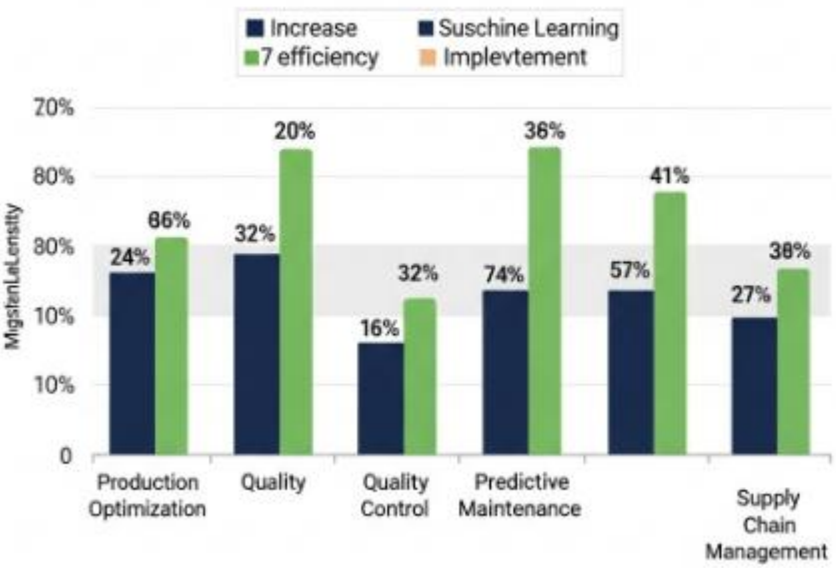

Fig: The Integration of Machine Learning to Streamline Manufacturing and Improve Quality Assurance.

5.6.1. Data Quality and Availability

The quality and volume of data available are the primary concern for a successful ML operation. The experience in recent years shows that the more data available during training, the better an ML-based application can perform in the production phase. The performance improvement usually comes along with better generalization when unseen data is fed after deployment. Previous studies show that for an ML project, the contribution of data quality, rather than its volume, outweighs the importance of the development algorithm and of the team and the amount of effort spent. Further, the cost of bad-quality data is five to ten times higher than the cost of obtaining high-quality data. However, a major obstacle to having enough quality data is monitoring in the manufacturing industry. While a lot of data is produced during the operation of industrial equipment, such data are sparse, have low sampling rates, and are often noisy, along with the difficulty of creating a ground truth for supervised learning. For some applications, it is even impossible to collect online data during equipment operation because of the risk of damaging the equipment or places of operation, which can be dangerous for people. The classical solution in that case is to use offline data, but such data might not be sufficient, or even impossible to obtain – even for estimates such as remaining useful life prediction, which require long data sequences. For some use cases, such data deficiency issues can somehow be verified in advance, but for those actual use cases and work conditions, data quality and availability are inevitable concerns for any ML-based solution in its development phase, and these concerns will determine the feasibility of setting up such a solution in practice.

5.6.2. Integration with Existing Systems

The integration of ML algorithms into existing quality assurance systems and processes is crucial for manufacturers. Existing quality assurance systems play a different role as compared to standard triggers for events such as receiving a train set that sounds different or has a different resonance frequency. In most cases, however, the existing system does not trigger any corrective actions but serves more as a passive reporting of quality issues. Often the existing systems will also confirm that there is an issue without determining the root cause of such an issue. However, simply reconciling the difference between existing triggers and ML insights is not enough. If an ML prediction does not trigger any corrective action, then should it become part of the existing quality assurance systems? Also, existing trigger reports are often unfounded. How can we be sure that when a report is issued, such a prediction is made in a responsible manner and provides trust within the department associated with making corrective actions? Further, if a manufacturer engages in continuous product improvement, can standard triggers for corrective actions continually issue reports over time? Integrating the quality assurance system with the ML algorithm has several advantages. The integration helps reduce the number of false alerts for quality impacts, which helps alleviate the fears of a production unit associated with triggering corrective actions each time the existing system detects a deviation. This eventually builds trust and helps in sharing and augmenting ML insights into the decision-making processes associated with corrective actions. Furthermore, integrating the insights from the existing warranty, repair, etc. systems into the ML training data set helps the ML algorithm better understand the impact of various features on the quality.

5.6.3. Skill Gaps and Training Needs

As the industrial ecosystem is rapidly changing and adapting to Industrial 4.0, companies face a challenge in finding skilled workers who can support their data science and machine learning initiatives. A large percentage of companies are struggling to recruit qualified candidates for their AI-related roles. This is attributed to the fact that new roles that have only recently emerged in AI or data science have nonetheless become especially crucial within a short time. These roles often come with very little guidance on what type of skills and proficiencies the person needs to do the work successfully, and this is exacerbated by the fact that there are not enough people entering the workforce with the necessary education or training.

Current deficiencies in education or skills can be addressed by either extending academic curricula to include them or providing alternative training and upskilling programs. Given the speed at which the AI and data landscape is maturing, academia is struggling to keep up. Additional challenges include re-streamlining programs so they support both graduate and non-graduate positions whilst also helping them to fill available roles in AI development and deployment. While traditional degrees will still be needed, the soft and hard skills required of a successful AI team member mean that organizations should also develop work-related training and mentorship programs marketed towards women, racial minorities, and veterans to help diversify the talent pool. Organizations can also fund initiatives where advanced degree students work on AI projects and close the gap that would otherwise exist.

5.7. Conclusion

This chapter discusses how soft-monitoring and machine-learning technologies applied to real-time process data can be used to help streamline manufacturing in automated production processes. Real-time process data can be effectively combined with close to real-time quality data to identify and track changes in the manufacturing process at the root cause level using soft sensors for those process change predictors that have been proven relevant. The disciplined process-integration approach leads to a better understanding of the process, more effective utilization of resources, continuous quality improvement, reduced cycle time, and reduced scrap and rework. These strategies can be applied to any automated process.

Machine learning and pattern recognition methods that have been proven highly effective in health monitoring and diagnostics can also be used to help manage the ramping up of automated processes. These machine learning methods can be used to link transient process behavior to the final quality of the manufactured product at the most granular level, which is the time-varying transient process data. Automated production processes mature extremely slowly, in some instances, since they are run on very long production cycles. Consequently, quality loss and scrap/rework loss accumulate over an extremely long time. Monitoring the transient process behavior at such a granular level represents an opportunity to reduce these losses. Such monitoring and diagnostics tools can also take advantage of the capability of pattern recognition tools to help automatically classify different types of transient behavior and help focus attention on those transients that are most predictive of final product quality. Such monitoring and diagnostics tools can help respond to the early signs of shifts in the relationship between transient process behavior and final product quality.

5.7.1. Future Trends

For a stable global economy, it is vital to increase the efficiency of production systems with the least consumption of resources. Manufacturing methods will deal with low lot sizes, rapid changes in production cycles, and dynamic networks. To continue being competitive, manufacturers will invest in automation technologies, like advanced robotics, computer-aided design and manufacturing, flexible manufacturing systems, manufacturing process integration, machine vision, quality improvement methods, rapid manufacturing tools, rapid transfer and repair, etc. Automation systems should be sophisticated enough to guide automatic cells to respond to the rapid change of articles in the market, varying cycle time, and production. This is only possible through the application of intelligent technologies or cyber-physical systems. Further, it has also been observed that with the explosion of big data in the manufacturing industry along with improvement in network bandwidth, product complexity is also increasing dramatically. It thus becomes important to consider models that allow for big data formation together with product complexity.

In addition, research institutions globally are focusing on developing newer models, solutions, and guidelines that would enable manufacturers to create cyber-physical systems that would fulfill their objectives. Furthermore, the next generation of manufacturing systems should be greener with a focus on decreasing negative impacts on the environment. Research in sustainable development strategies has opened new horizons for enhancing the use of green manufacturing technologies with negligible non-renewable resources and energy. Further, green machine learning technology can act as a catalyst in developing renewable products with zero feedback that would thus require less energy and improve quality assurance with minimal human intervention. This would then ensure that the future of manufacturing is responsible towards the utilization of resources.

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